autogluon_each_location

October 26, 2023

1 Config

[1]:
```
# config

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*10
presets = "best_quality"#'best_quality'

do_drop_ds = True
# hour, dayofweek, dayofmonth, month, year
use_dt_attrs = []#["hour", "year"]
use_estimated_diff_attr = False
use_is_estimated_attr = True

drop_night_outliers = True
drop_null_outliers = True

to_drop = ["snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:ms",␣
 ↪"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:cm",␣
 ↪"wind_speed_u_10m:ms", "wind_speed_v_10m:ms", "snow_melt_10min:mm",␣
 ↪"rain_water:kgm2", "dew_point_2m:K", "precip_5min:mm", "absolute_humidity_2m:
 ↪gm3", "air_density_2m:kgm3"]#, "msl_pressure:hPa", "pressure_50m:hPa", ␣
 ↪"pressure_100m:hPa"]

#to_drop = ["snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:
 ↪ms",␣"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:
 ↪cm",␣"wind_speed_u_10m:ms", "wind_speed_v_10m:ms", "snow_melt_10min:
 ↪mm",␣"rain_water:kgm2", "dew_point_2m:K", "precip_5min:mm",␣
 ↪"absolute_humidity_2m:gm3", "air_density_2m:kgm3"]

use_groups = False
n_groups = 8

# auto_stack = True
num_stack_levels = 0
num_bag_folds = None# 8
```

```
num_bag_sets = None#20

use_tune_data = True
use_test_data = True
#tune_and_test_length = 0.5 # 3 months from end
# holdout_frac = None
use_bag_holdout = True # Enable this if there is a large gap between score_val␣
↪and score_test in stack models.

sample_weight = None#'sample_weight' #None
weight_evaluation = False#
sample_weight_estimated = 1
sample_weight_may_july = 1

run_analysis = False

shift_predictions_by_average_of_negatives_then_clip = False
clip_predictions = True
shift_predictions = False
```

2 Loading and preprocessing

[2]:
```
import pandas as pd
import numpy as np



import warnings
warnings.filterwarnings("ignore")


def feature_engineering(X):
    # shift all columns with "1h" in them by 1 hour, so that for index 16:00,␣
↪we have the values from 17:00
    # but only for the columns with "1h" in the name
    #X_shifted = X.filter(regex="\dh").shift(-1, axis=1)
    #print(f"Number of columns with 1h in name: {X_shifted.columns}")


    columns = ['clear_sky_energy_1h:J', 'diffuse_rad_1h:J', 'direct_rad_1h:J',
               'fresh_snow_12h:cm', 'fresh_snow_1h:cm', 'fresh_snow_24h:cm',
               'fresh_snow_3h:cm', 'fresh_snow_6h:cm']

    # Filter rows where index.minute == 0
    X_shifted = X[X.index.minute == 0][columns].copy()
```

```
    # Create a set for constant-time lookup
    index_set = set(X.index)

    # Vectorized time shifting
    one_hour = pd.Timedelta('1 hour')
    shifted_indices = X_shifted.index + one_hour
    X_shifted.loc[shifted_indices.isin(index_set)] = X.
 ↪loc[shifted_indices[shifted_indices.isin(index_set)]][columns]

    # Count
    count1 = len(shifted_indices[shifted_indices.isin(index_set)])
    count2 = len(X_shifted) - count1

    print("COUNT1", count1)
    print("COUNT2", count2)

    # Rename columns
    X_old_unshifted = X_shifted.copy()
    X_old_unshifted.columns = [f"{col}_not_shifted" for col in X_old_unshifted.
 ↪columns]

    date_calc = None
    # If 'date_calc' is present, handle it
    if 'date_calc' in X.columns:
        date_calc = X[X.index.minute == 0]['date_calc']




    # resample to hourly
    print("index: ", X.index[0])
    X = X.resample('H').mean()
    print("index AFTER: ", X.index[0])

    X[columns] = X_shifted[columns]
    #X[X_old_unshifted.columns] = X_old_unshifted

    if date_calc is not None:
        X['date_calc'] = date_calc

    return X




def fix_X(X, name):
```

```python
    # Convert 'date_forecast' to datetime format and replace original column
    ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)


    X = feature_engineering(X)

    return X



def handle_features(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_X(X_train_observed, "X_train_observed")
    X_train_estimated = fix_X(X_train_estimated, "X_train_estimated")
    X_test = fix_X(X_test, "X_test")


    if weight_evaluation:
        # add sample weights, which are 1 for observed and 3 for estimated
        X_train_observed["sample_weight"] = 1
        X_train_estimated["sample_weight"] = sample_weight_estimated
        X_test["sample_weight"] = sample_weight_estimated


    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train,
 ↪location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train =
 ↪handle_features(X_train_observed, X_train_estimated, X_test, y_train)

    if use_estimated_diff_attr:
        X_train_observed["estimated_diff_hours"] = 0
        X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index -
 ↪pd.to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
```

```python
        X_test["estimated_diff_hours"] = (X_test.index - pd.to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

        X_train_estimated["estimated_diff_hours"] = X_train_estimated["estimated_diff_hours"].astype('int64')
        # the filled once will get dropped later anyways, when we drop y nans
        X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].fillna(-50).astype('int64')

    if use_is_estimated_attr:
        X_train_observed["is_estimated"] = 0
        X_train_estimated["is_estimated"] = 1
        X_test["is_estimated"] = 1


    # drop date_calc
    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)


    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True, right_index=True)

    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")

    print(f"Size of estimated after dropping nans: {len(X_train[X_train['is_estimated']==1].dropna(subset=['y']))}")


    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
```

```python
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
 ↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
COUNT1 29667
COUNT2 1
index:  2019-06-02 22:00:00
index AFTER:  2019-06-02 22:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 0
Size of estimated after dropping nans: 4418
Processing location B…
COUNT1 29232
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
```

```
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 4
Size of estimated after dropping nans: 3625
Processing location C…
COUNT1 29206
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 6059
Size of estimated after dropping nans: 2954
```

2.1 Feature enginering

2.1.1 Remove anomalies

[3]:
```python
import numpy as np
import pandas as pd


# loop thorugh x train[y], keep track of streaks of same values and replace␣
↪them with nan if they are too long
# also replace nan with 0

import numpy as np

def replace_streaks_with_nan(df, max_streak_length, column="y"):
    for location in df["location"].unique():
        x = df[df["location"] == location][column].copy()

        last_val = None
        streak_length = 1
        streak_indices = []
        allowed = [0]
        found_streaks = {}
```

```
        for idx in x.index:
            value = x[idx]
            # if location == "B":
            #     continue

            if value == last_val and value not in allowed:
                streak_length += 1
                streak_indices.append(idx)
            else:
                streak_length = 1
                last_val = value
                streak_indices.clear()

            if streak_length > max_streak_length:
                found_streaks[value] = streak_length

                for streak_idx in streak_indices:
                    x[idx] = np.nan
                streak_indices.clear()  # clear after setting to NaN to avoid␣
 ↪setting multiple times
        df.loc[df["location"] == location, column] = x

        print(f"Found streaks for location {location}: {found_streaks}")

    return df


# deep copy of X_train into x_copy
X_train = replace_streaks_with_nan(X_train.copy(), 3, "y")
```

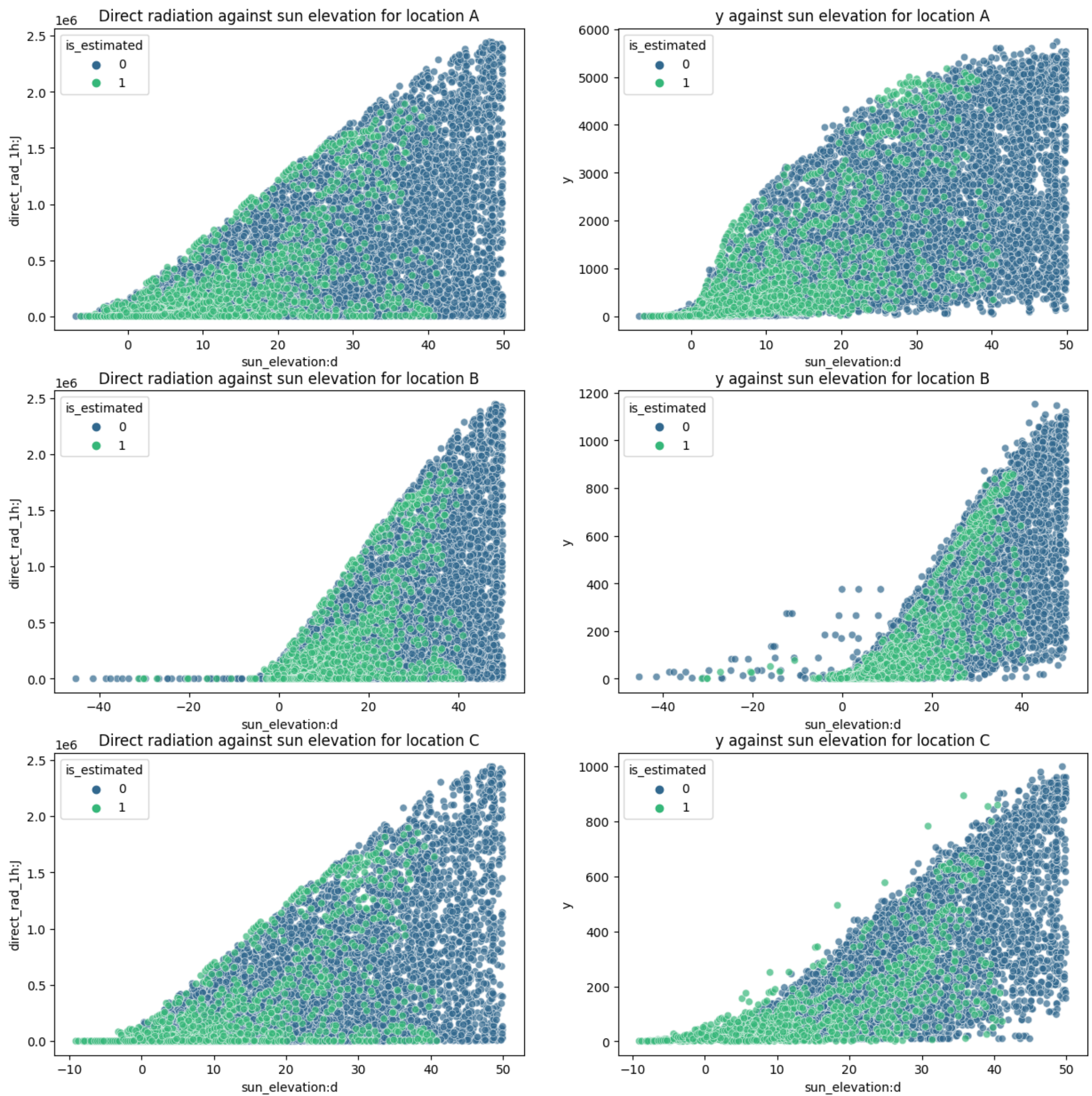
```
Found streaks for location A: {}
Found streaks for location B: {3.45: 28, 6.9: 7, 12.9375: 5, 13.8: 8, 276.0: 78,
18.975: 58, 0.8625: 4, 118.1625: 33, 34.5: 11, 183.7125: 1058, 87.1125: 7,
79.35: 34, 7.7625: 12, 27.6: 448, 273.41249999999997: 72, 264.78749999999997:
55, 169.05: 33, 375.1875: 56, 314.8125: 66, 76.7625: 10, 135.4125: 216, 81.9375:
202, 2.5875: 12, 81.075: 210}
Found streaks for location C: {9.8: 4, 29.400000000000002: 4, 19.6: 4}
```

[4]:
```
# print num rows
temprows = len(X_train)
X_train.dropna(subset=['y', 'direct_rad_1h:J', 'diffuse_rad_1h:J'],␣
 ↪inplace=True)
print("Dropped rows: ", temprows - len(X_train))
```

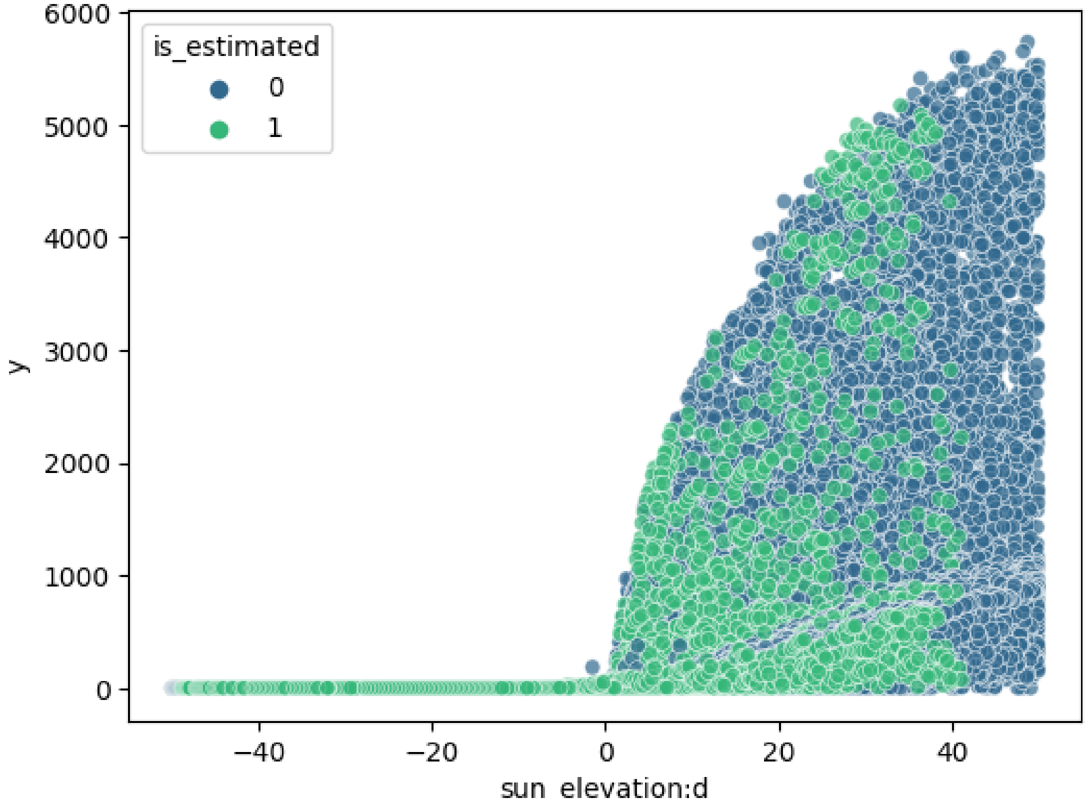
```
Dropped rows:  9293
```

[5]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
# Filter out rows where y == 0
temp = X_train[X_train["y"] != 0]

# Plotting
fig, axes = plt.subplots(len(locations), 2, figsize=(15, 5 * len(locations)))

for idx, location in enumerate(locations):
    sns.scatterplot(ax=axes[idx][0], data=temp[temp["location"] == location], x="sun_elevation:d", y="direct_rad_1h:J", hue="is_estimated", palette="viridis", alpha=0.7)
    axes[idx][0].set_title(f"Direct radiation against sun elevation for location {location}")

    sns.scatterplot(ax=axes[idx][1], data=temp[temp["location"] == location], x="sun_elevation:d", y="y", hue="is_estimated", palette="viridis", alpha=0.7)
    axes[idx][1].set_title(f"y against sun elevation for location {location}")

# plt.tight_layout()
# plt.show()
```

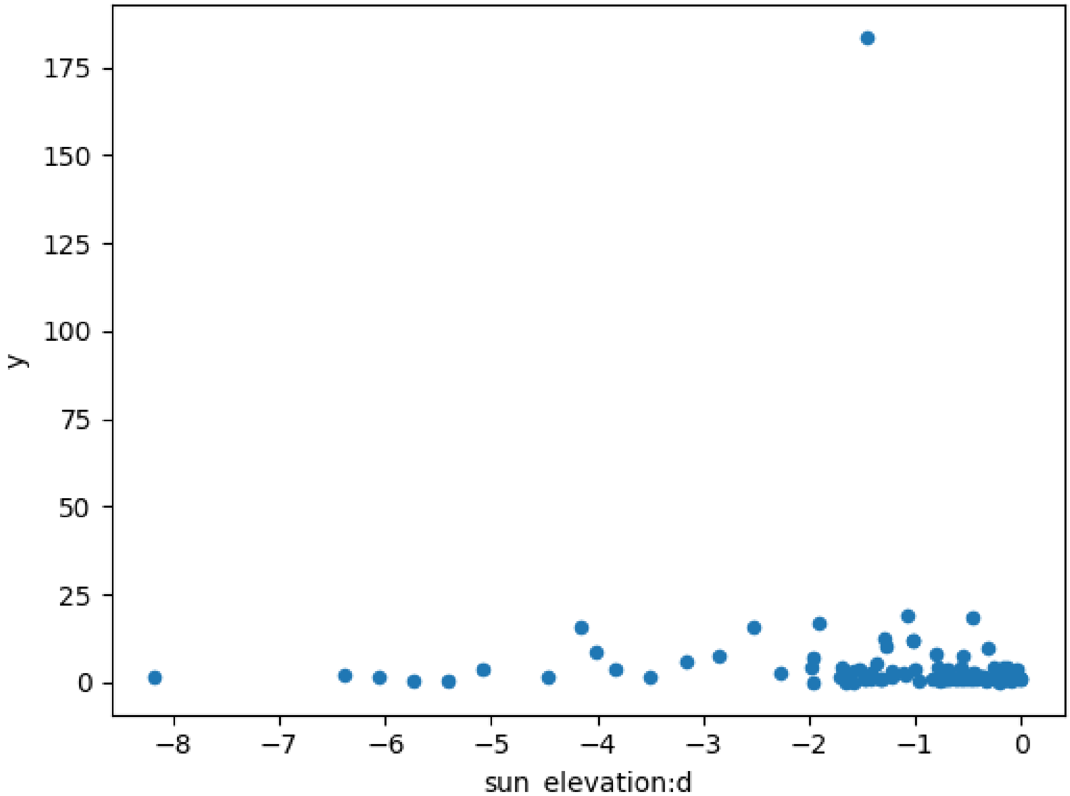


[6]:
```
thresh = 0.1

# Update "y" values to NaN if they don't meet the criteria
mask = (X_train["direct_rad_1h:J"] <= thresh) & (X_train["diffuse_rad_1h:J"] <= thresh) & (X_train["y"] >= 0.1)
if drop_night_outliers:
    X_train.loc[mask, "y"] = np.nan

# Plot using sns scatterplot
sns.scatterplot(data=X_train, x="sun_elevation:d", y="y", hue="is_estimated", palette="viridis", alpha=0.7)
plt.show()
```



[7]:
```
# location B count number of rows with y > 0 and sun_elevation:d < 0

condition = (X_train["location"] == "B") & (X_train["y"] > 0) &␣
 ↪(X_train["sun_elevation:d"] < 0)
bad = X_train[condition]

bad.plot.scatter(x="sun_elevation:d", y="y")
```

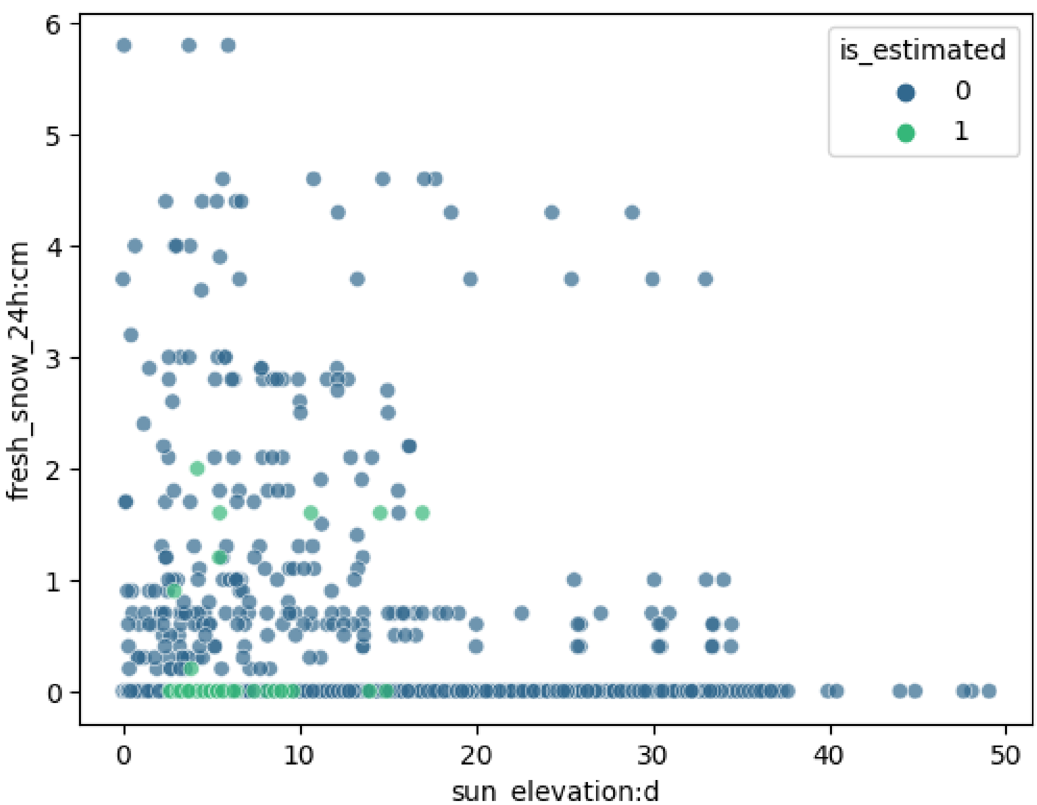
[7]: <AxesSubplot: xlabel='sun_elevation:d', ylabel='y'>



[8]:
```
# set y to nan where y is 0, but direct_rad_1h:J or diffuse_rad_1h:J are > 0␣
↪(or some threshold)
threshold_direct = X_train["direct_rad_1h:J"].max() * 0.01
threshold_diffuse = X_train["diffuse_rad_1h:J"].max() * 0.01
print(f"Threshold direct: {threshold_direct}")
print(f"Threshold diffuse: {threshold_diffuse}")

mask = (X_train["y"] == 0) & ((X_train["direct_rad_1h:J"] > threshold_direct) |␣
↪(X_train["diffuse_rad_1h:J"] > threshold_diffuse)) & (X_train["sun_elevation:
↪d"] > 0) & (X_train["fresh_snow_24h:cm"] < 6) & (X_train[['fresh_snow_12h:
↪cm', 'fresh_snow_1h:cm',  'fresh_snow_3h:cm', 'fresh_snow_6h:cm']].
↪sum(axis=1) == 0)
print(len(X_train[mask]))

#print(X_train[mask][[x for x in X_train.columns if "snow" in x]])

# show plot where mask is true
#sns.scatterplot(data=X_train[mask], x="sun_elevation:d", y="y",␣
↪hue="is_estimated", palette="viridis", alpha=0.7)
```

```python
sns.scatterplot(data=X_train[mask], x="sun_elevation:d", y="fresh_snow_24h:cm",␣
↪hue="is_estimated", palette="viridis", alpha=0.7)
plt.show()

#sns.scatterplot(data=X_train[mask], x="fresh_snow_24h:cm",␣
↪y="total_cloud_cover:p", hue="is_estimated", palette="viridis", alpha=0.7)



# set y to nan where mask
if drop_null_outliers:
    X_train.loc[mask, "y"] = np.nan

# show how many rows for each location, and for estimated and not estimated
X_train[mask].groupby(["location", "is_estimated"]).count()["direct_rad_1h:J"]
```

```
Threshold direct: 24458.97
Threshold diffuse: 11822.505000000001
2599
```



[8]:
```
location  is_estimated
A         0                 87
          1                 10
B         0               1250
          1                 32
C         0               1174
          1                 46
Name: direct_rad_1h:J, dtype: int64
```

[9]:
```
# print num rows
temprows = len(X_train)
X_train.dropna(subset=['y', 'direct_rad_1h:J', 'diffuse_rad_1h:J'],␣
↪inplace=True)
print("Dropped rows: ", temprows - len(X_train))
```

```
Dropped rows:  4475
```

2.1.2 Other stuff

[10]:
```
import numpy as np
import pandas as pd

for attr in use_dt_attrs:
    X_train[attr] = getattr(X_train.index, attr)
    X_test[attr] = getattr(X_test.index, attr)

#print(X_train.head())


# If the "sample_weight" column is present and weight_evaluation is True,␣
↪multiply sample_weight with sample_weight_may_july if the ds is between␣
↪05-01 00:00:00 and 07-03 23:00:00, else add sample_weight as a column to␣
↪X_train
if weight_evaluation:
    if "sample_weight" not in X_train.columns:
        X_train["sample_weight"] = 1

    X_train.loc[((X_train.index.month >= 5) & (X_train.index.month <= 6)) |␣
↪((X_train.index.month == 7) & (X_train.index.day <= 3)), "sample_weight"] *=␣
↪sample_weight_may_july


print(X_train.iloc[200])
print(X_train[((X_train.index.month >= 5) & (X_train.index.month <= 6)) |␣
↪((X_train.index.month == 7) & (X_train.index.day <= 3))].head(1))
```

```
if use_groups:
    # fix groups for cross validation
    locations = X_train['location'].unique()  # Assuming 'location' is the name␣
 ↪of the column representing locations

    grouped_dfs = []  # To store data frames split by location

    # Loop through each unique location
    for loc in locations:
        loc_df = X_train[X_train['location'] == loc]

        # Sort the DataFrame for this location by the time column
        loc_df = loc_df.sort_index()

        # Calculate the size of each group for this location
        group_size = len(loc_df) // n_groups

        # Create a new 'group' column for this location
        loc_df['group'] = np.repeat(range(n_groups),␣
 ↪repeats=[group_size]*(n_groups-1) + [len(loc_df) - group_size*(n_groups-1)])

        # Append to list of grouped DataFrames
        grouped_dfs.append(loc_df)

    # Concatenate all the grouped DataFrames back together
    X_train = pd.concat(grouped_dfs)
    X_train.sort_index(inplace=True)
    print(X_train["group"].head())






X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

```
absolute_humidity_2m:gm3              8.85
air_density_2m:kgm3                  1.223
ceiling_height_agl:m           3206.774902
clear_sky_energy_1h:J          1687762.375
clear_sky_rad:W                 576.825012
cloud_base_agl:m               3206.774902
dew_or_rime:idx                        0.0
```

```
dew_point_2m:K                      282.625
diffuse_rad:W                        164.75
diffuse_rad_1h:J               473465.40625
direct_rad:W                     265.799988
direct_rad_1h:J                 875466.3125
effective_cloud_cover:p           54.775002
elevation:m                             6.0
fresh_snow_12h:cm                       0.0
fresh_snow_1h:cm                        0.0
fresh_snow_24h:cm                       0.0
fresh_snow_3h:cm                        0.0
fresh_snow_6h:cm                        0.0
is_day:idx                              1.0
is_in_shadow:idx                        0.0
msl_pressure:hPa                1024.849976
precip_5min:mm                          0.0
precip_type_5min:idx                    0.0
pressure_100m:hPa               1011.849976
pressure_50m:hPa                1017.849976
prob_rime:p                             0.0
rain_water:kgm2                         0.0
relative_humidity_1000hPa:p       65.349998
sfc_pressure:hPa                1023.900024
snow_density:kgm3                       NaN
snow_depth:cm                           0.0
snow_drift:idx                          0.0
snow_melt_10min:mm                      0.0
snow_water:kgm2                         0.0
sun_azimuth:d                    107.550003
sun_elevation:d                   34.256001
super_cooled_liquid_water:kgm2          0.0
t_1000hPa:K                      286.774994
total_cloud_cover:p               82.199997
visibility:m                   48704.824219
wind_speed_10m:ms                       2.7
wind_speed_u_10m:ms                    -2.4
wind_speed_v_10m:ms                    -1.2
wind_speed_w_1000hPa:ms                 0.0
is_estimated                              0
y                                    1828.2
location                                  A
Name: 2019-06-12 07:00:00, dtype: object
                     absolute_humidity_2m:gm3  air_density_2m:kgm3  \
ds
2019-06-02 23:00:00                       7.7               1.2235

                     ceiling_height_agl:m  clear_sky_energy_1h:J  \
ds
```

```
2019-06-02 23:00:00           1689.824951                   0.0

                     clear_sky_rad:W  cloud_base_agl:m  dew_or_rime:idx  \
ds
2019-06-02 23:00:00              0.0       1689.824951              0.0

                     dew_point_2m:K  diffuse_rad:W  diffuse_rad_1h:J  …  \
ds                                                                   …
2019-06-02 23:00:00      280.299988            0.0               0.0  …

                     t_1000hPa:K  total_cloud_cover:p  visibility:m  \
ds
2019-06-02 23:00:00   286.899994                100.0  33770.648438

                     wind_speed_10m:ms  wind_speed_u_10m:ms  \
ds
2019-06-02 23:00:00               3.35                -3.35

                     wind_speed_v_10m:ms  wind_speed_w_1000hPa:ms  \
ds
2019-06-02 23:00:00                0.275                      0.0

                     is_estimated    y  location
ds
2019-06-02 23:00:00             0  0.0         A

[1 rows x 48 columns]
```

[11]:

```
# Create a plot of X_train showing its "y" and color it based on the value of␣
↪the sample_weight column.
if "sample_weight" in X_train.columns:
    import matplotlib.pyplot as plt
    import seaborn as sns
    sns.scatterplot(data=X_train, x=X_train.index, y="y", hue="sample_weight",␣
↪palette="deep", size=3)
    plt.show()
```

[12]:

```
def normalize_sample_weights_per_location(df):
    for loc in locations:
        loc_df = df[df["location"] == loc]
        loc_df["sample_weight"] = loc_df["sample_weight"] /␣
↪loc_df["sample_weight"].sum() * loc_df.shape[0]
        df[df["location"] == loc] = loc_df
    return df

import pandas as pd
```

```python
def split_and_shuffle_data(input_data, num_bins, frac1):
    """
    Splits the input_data into num_bins and shuffles them, then divides the
 ↪bins into two datasets based on the given fraction for the first set.

    Args:
        input_data (pd.DataFrame): The data to be split and shuffled.
        num_bins (int): The number of bins to split the data into.
        frac1 (float): The fraction of each bin to go into the first output
 ↪dataset.

    Returns:
        pd.DataFrame, pd.DataFrame: The two output datasets.
    """
    # Validate the input fraction
    if frac1 < 0 or frac1 > 1:
        raise ValueError("frac1 must be between 0 and 1.")

    if frac1==1:
        return input_data, pd.DataFrame()

    # Calculate the fraction for the second output set
    frac2 = 1 - frac1

    # Calculate bin size
    bin_size = len(input_data) // num_bins

    # Initialize empty DataFrames for output
    output_data1 = pd.DataFrame()
    output_data2 = pd.DataFrame()

    for i in range(num_bins):
        # Shuffle the data in the current bin
        np.random.seed(i)
        current_bin = input_data.iloc[i * bin_size: (i + 1) * bin_size].
 ↪sample(frac=1)

        # Calculate the sizes for each output set
        size1 = int(len(current_bin) * frac1)

        # Split and append to output DataFrames
        output_data1 = pd.concat([output_data1, current_bin.iloc[:size1]])
        output_data2 = pd.concat([output_data2, current_bin.iloc[size1:]])

    # Shuffle and split the remaining data
    remaining_data = input_data.iloc[num_bins * bin_size:].sample(frac=1)
```

```
    remaining_size1 = int(len(remaining_data) * frac1)

    output_data1 = pd.concat([output_data1, remaining_data.iloc[:
↪remaining_size1]])
    output_data2 = pd.concat([output_data2, remaining_data.iloc[remaining_size1:
↪]])

    return output_data1, output_data2
```

[13]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
data = TabularDataset('X_train_raw.csv')
# set group column of train_data be increasing from 0 to 7 based on time, the␣
↪first 1/8 of the data is group 0, the second 1/8 of the data is group 1, etc.
data['ds'] = pd.to_datetime(data['ds'])
data = data.sort_values(by='ds')

# # print size of the group for each location
# for loc in locations:
#     print(f"Location {loc}:")
#     print(train_data[train_data["location"] == loc].groupby('group').size())


# get end date of train data and subtract 3 months
#split_time = pd.to_datetime(train_data["ds"]).max() - pd.
↪Timedelta(hours=tune_and_test_length)
# 2022-10-28 22:00:00
split_time = pd.to_datetime("2022-10-28 22:00:00")
train_set = TabularDataset(data[data["ds"] < split_time])
estimated_set = TabularDataset(data[data["ds"] >= split_time]) # only estimated

test_set = pd.DataFrame()
tune_set = pd.DataFrame()
new_train_set = pd.DataFrame()

if not use_tune_data:
    raise Exception("Not implemented")

for location in locations:
    loc_data = data[data["location"] == location]
    num_train_rows = len(loc_data)

    tune_rows = 1500.0 # 2500.0
    if use_test_data:
        tune_rows = 1880.0#max(3000.0,␣
↪len(estimated_set[estimated_set["location"] == location]))
```

```
    holdout_frac = max(0.01, min(0.1, tune_rows / num_train_rows)) *␣
↪num_train_rows / len(estimated_set[estimated_set["location"] == location])

    print(f"Size of estimated for location {location}:␣
↪{len(estimated_set[estimated_set['location'] == location])}. Holdout frac␣
↪should be % of estimated: {holdout_frac}")

    # shuffle and split data
    loc_tune_set, loc_new_train_set =␣
↪split_and_shuffle_data(estimated_set[estimated_set['location'] == location],␣
↪40, holdout_frac)
    print(f"Length of location tune set : {len(loc_tune_set)}")
    new_train_set = pd.concat([new_train_set, loc_new_train_set])

    if use_test_data:
        loc_test_set, loc_tune_set = split_and_shuffle_data(loc_tune_set, 40, 0.
↪2)
        test_set = pd.concat([test_set, loc_test_set])

    tune_set = pd.concat([tune_set, loc_tune_set])




print("Length of train set before adding test set", len(train_set))
# add rest to train_set
train_set = pd.concat([train_set, new_train_set])
print("Length of train set after adding test set", len(train_set))




if use_groups:
    test_set = test_set.drop(columns=['group'])


tuning_data = tune_set

# number of rows in tuning data for each location
print("Shapes of tuning data", tuning_data.groupby('location').size())



if use_test_data:
    test_data = test_set
    print("Shape of test", test_data.shape[0])
```

```
train_data = train_set

# ensure sample weights for your training (or tuning) data sum to the number of␣
↪rows in the training (or tuning) data.
if weight_evaluation:
    # ensure sample weights for data sum to the number of rows in the tuning /
↪train data.
    tuning_data = normalize_sample_weights_per_location(tuning_data)
    train_data = normalize_sample_weights_per_location(train_data)
    if use_test_data:
        test_data = normalize_sample_weights_per_location(test_data)


train_data = TabularDataset(train_data)
tuning_data = TabularDataset(tuning_data)

if use_test_data:
    test_data = TabularDataset(test_data)
```

```
Size of estimated for location A: 4204. Holdout frac should be % of estimated:
0.44719314938154137
Length of location tune set : 1841
Size of estimated for location B: 3501. Holdout frac should be % of estimated:
0.5369894315909739
Length of location tune set : 1851
Size of estimated for location C: 2877. Holdout frac should be % of estimated:
0.6534584636774418
Length of location tune set : 1864
Length of train set before adding test set 74736
Length of train set after adding test set 79762
Shapes of tuning data location
A    1481
B    1489
C    1500
dtype: int64
Shape of test 1086
```

3 Quick EDA

[14]:
```
if run_analysis:
    import autogluon.eda.auto as auto
    auto.dataset_overview(train_data=train_data, test_data=test_data,␣
↪label="y", sample=None)
```

[15]:
```
if run_analysis:
    auto.target_analysis(train_data=train_data, label="y", sample=None)
```

4 Modeling

[16]:
```python
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 115
Now creating submission number: 116
New filename: submission_116
```

[17]:
```python
predictors = [None, None, None]
```

[18]:
```python
def fit_predictor_for_location(loc):
    print(f"Training model for location {loc}...")
    # sum of sample weights for this location, and number of rows, for both␣
↪train and tune data and test data
    if weight_evaluation:
        print("Train data sample weight sum:",␣
↪train_data[train_data["location"] == loc]["sample_weight"].sum())
        print("Train data number of rows:", train_data[train_data["location"]␣
↪== loc].shape[0])
        if use_tune_data:
            print("Tune data sample weight sum:",␣
↪tuning_data[tuning_data["location"] == loc]["sample_weight"].sum())
            print("Tune data number of rows:",␣
↪tuning_data[tuning_data["location"] == loc].shape[0])
        if use_test_data:
            print("Test data sample weight sum:",␣
↪test_data[test_data["location"] == loc]["sample_weight"].sum())
            print("Test data number of rows:", test_data[test_data["location"]␣
↪== loc].shape[0])
    predictor = TabularPredictor(
        label=label,
```

```
        eval_metric=metric,
        path=f"AutogluonModels/{new_filename}_{loc}",
        # sample_weight=sample_weight,
        # weight_evaluation=weight_evaluation,
        # groups="group" if use_groups else None,
    ).fit(
        train_data=train_data[train_data["location"] == loc].
↪drop(columns=["ds"]),
        time_limit=time_limit,
        presets=presets,
        num_stack_levels=num_stack_levels,
        num_bag_folds=num_bag_folds if not use_groups else 2,# just put␣
↪somethin, will be overwritten anyways
        num_bag_sets=num_bag_sets,
        tuning_data=tuning_data[tuning_data["location"] == loc].
↪reset_index(drop=True).drop(columns=["ds"]) if use_tune_data else None,
        use_bag_holdout=use_bag_holdout,
        # holdout_frac=holdout_frac,
    )

    # evaluate on test data
    if use_test_data:
        # drop sample_weight column
        t = test_data[test_data["location"] == loc]#.
↪drop(columns=["sample_weight"])
        perf = predictor.evaluate(t)
        print("Evaluation on test data:")
        print(perf[predictor.eval_metric.name])

    return predictor

loc = "A"
predictors[0] = fit_predictor_for_location(loc)
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=0, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 600s
AutoGluon will save models to "AutogluonModels/submission_116_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   194.55 GB / 315.93 GB (61.6%)
Train Data Rows:    30842
Train Data Columns: 32
```

```
Tuning Data Rows:    1481
Tuning Data Columns: 32
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 674.96597,
1197.37164)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    132446.04 MB
        Train Data (Original)  Memory Usage: 9.89 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…

Training model for location A…

        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', ['bool']) :  1 | ['is_estimated']
        0.1s = Fit runtime
```

```
        30 features in original data used to generate 30 features in processed
data.
        Train Data (Processed) Memory Usage: 7.53 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.15s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 599.85s of the
599.85s of remaining time.
        -192.5056        = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.37s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 599.36s of the
599.36s of remaining time.
        -194.3426        = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.37s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 598.9s of the
598.9s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -91.2719         = Validation score   (-mean_absolute_error)
```

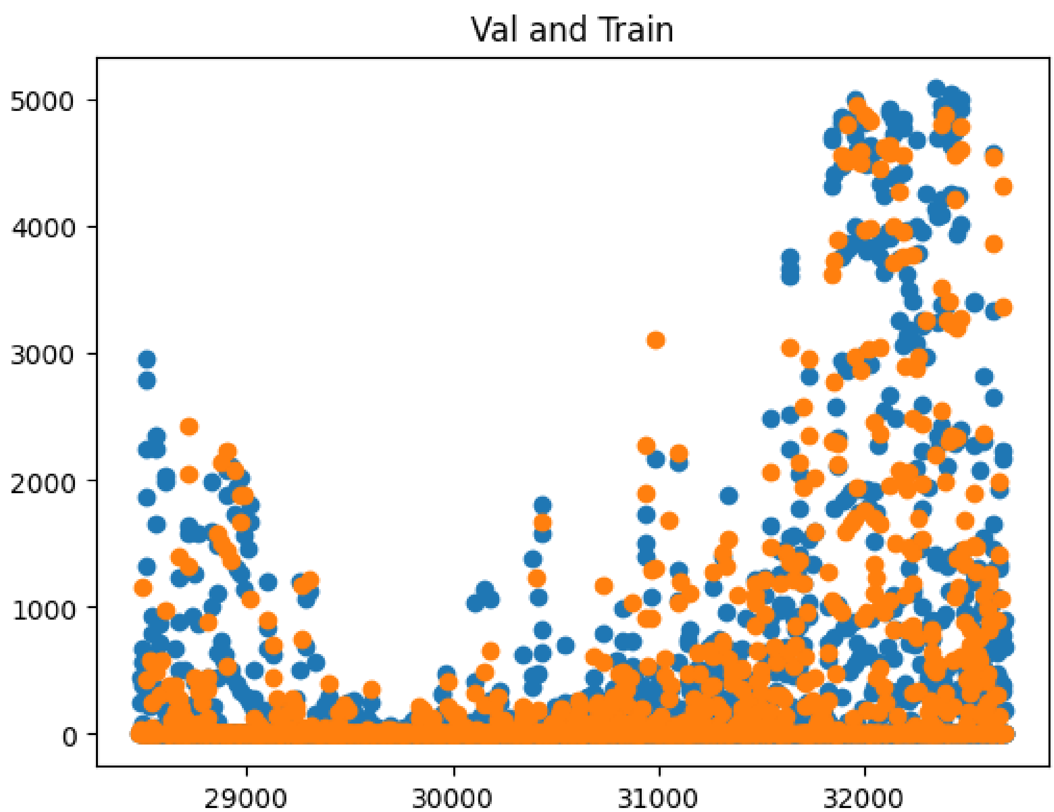
```
        28.15s   = Training   runtime
        16.98s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 561.3s of the 561.3s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -101.1843       = Validation score   (-mean_absolute_error)
        20.01s   = Training   runtime
        2.61s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 538.35s of
the 538.35s of remaining time.
        -109.331        = Validation score   (-mean_absolute_error)
        7.16s    = Training   runtime
        1.05s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 528.99s of the
528.99s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -107.41  = Validation score   (-mean_absolute_error)
        189.88s  = Training   runtime
        0.09s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 337.97s of the
337.97s of remaining time.
        -112.8359       = Validation score   (-mean_absolute_error)
        1.42s    = Training   runtime
        1.04s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 334.36s of
the 334.35s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -112.9022       = Validation score   (-mean_absolute_error)
        39.22s   = Training   runtime
        0.48s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 292.47s of the
292.47s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -106.5069       = Validation score   (-mean_absolute_error)
        7.9s     = Training   runtime
        0.32s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 282.44s of the
282.44s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -94.4412        = Validation score   (-mean_absolute_error)
        128.35s  = Training   runtime
        0.32s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 152.67s of the
```

```
152.67s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -98.4742         = Validation score   (-mean_absolute_error)
        92.28s   = Training   runtime
        26.66s   = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
49.71s of remaining time.
        -88.8815         = Validation score   (-mean_absolute_error)
        0.42s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 550.81s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_116_A/")
Evaluation: mean_absolute_error on test data: -87.45214541418483
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -87.45214541418483,
    "root_mean_squared_error": -265.60417654453016,
    "mean_squared_error": -70545.57859789794,
    "r2": 0.9218862757955032,
    "pearsonr": 0.9605260607641231,
    "median_absolute_error": -2.8622360229492188
}

Evaluation on test data:
-87.45214541418483
```

[19]:

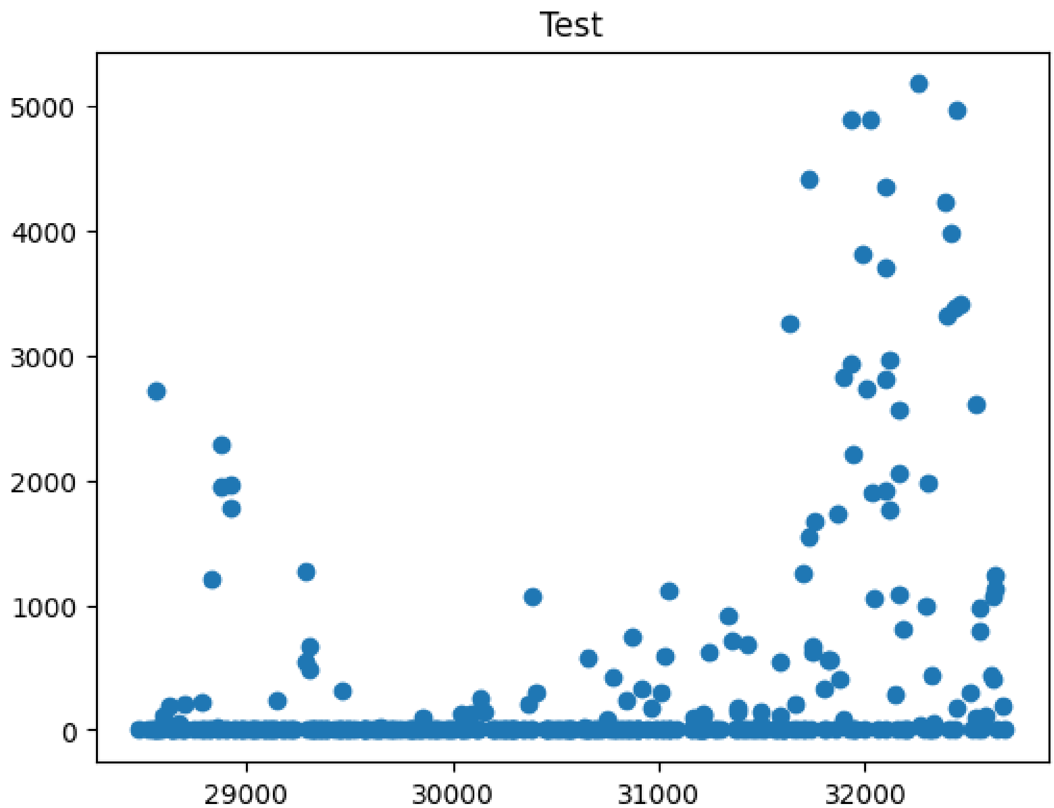
```
import matplotlib.pyplot as plt
leaderboards = [None, None, None]
def leaderboard_for_location(i, loc):
    if use_tune_data:
        plt.scatter(train_data[(train_data["location"] == loc) &
 ↪(train_data["is_estimated"]==True)]["y"].index,
 ↪train_data[(train_data["location"] == loc) &
 ↪(train_data["is_estimated"]==True)]["y"])
        plt.scatter(tuning_data[tuning_data["location"] == loc]["y"].index,
 ↪tuning_data[tuning_data["location"] == loc]["y"])
        plt.title("Val and Train")
        plt.show()

        if use_test_data:
            lb = predictors[i].leaderboard(test_data[test_data["location"] ==
 ↪loc])
```

```
            lb["location"] = loc
            plt.scatter(test_data[test_data["location"] == loc]["y"].index,␣
↪test_data[test_data["location"] == loc]["y"])
            plt.title("Test")

            return lb

    return pd.DataFrame()

leaderboards[0] = leaderboard_for_location(0, loc)
```




```
                    model  score_test   score_val  pred_time_test
pred_time_val    fit_time  pred_time_test_marginal  pred_time_val_marginal
fit_time_marginal  stack_level  can_infer  fit_order
0         LightGBMXT_BAG_L1  -85.653621  -91.271933        0.920395
16.977771   28.148052                 0.920395              16.977771
28.148052            1       True          3
1       WeightedEnsemble_L2  -87.452145  -88.881501        1.074398
17.296977  156.915241                 0.003499               0.000659
0.415119             2       True         12
2      LightGBMLarge_BAG_L1  -95.107791  -98.474240        3.284012
```

```
26.660846   92.283242                3.284012               26.660846
92.283242            1       True         11
3          LightGBM_BAG_L1  -97.939220 -101.184336        0.352891
2.606017   20.010375                0.352891                2.606017
20.010375            1       True          4
4    NeuralNetTorch_BAG_L1 -101.944230  -94.441176        0.150504
0.318547  128.352071                0.150504                0.318547
128.352071            1       True         10
5          CatBoost_BAG_L1 -106.773532 -107.409980        0.063859
0.088434  189.879921                0.063859                0.088434
189.879921            1       True          6
6     ExtraTreesMSE_BAG_L1 -107.563621 -112.835915        0.564387
1.040675    1.416519                0.564387                1.040675
1.416519            1       True          7
7           XGBoost_BAG_L1 -108.915558 -106.506926        0.126528
0.315428    7.896552                0.126528                0.315428
7.896552            1       True          9
8   RandomForestMSE_BAG_L1 -110.304078 -109.331006        0.584841
1.053334    7.164977                0.584841                1.053334
7.164977            1       True          5
9   NeuralNetFastAI_BAG_L1 -112.878491 -112.902190        0.183729
0.481372   39.217984                0.183729                0.481372
39.217984            1       True          8
10   KNeighborsUnif_BAG_L1 -213.291654 -192.505644        0.168644
0.365585    0.031718                0.168644                0.365585
0.031718            1       True          1
11   KNeighborsDist_BAG_L1 -214.175452 -194.342637        0.011993
0.365703    0.030219                0.011993                0.365703
0.030219            1       True          2
```



[20]:
```
loc = "B"
predictors[1] = fit_predictor_for_location(loc)
leaderboards[1] = leaderboard_for_location(1, loc)
```

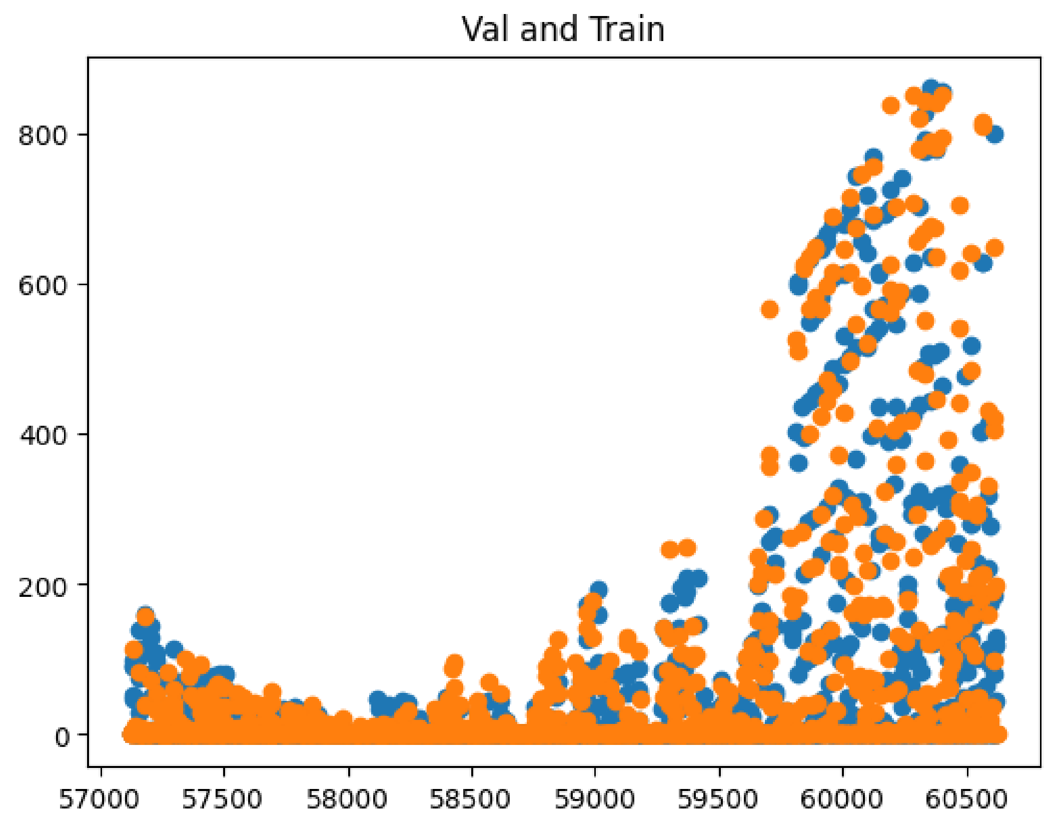
```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=0, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 600s
AutoGluon will save models to "AutogluonModels/submission_116_B/"
AutoGluon Version:  0.8.2

Training model for location B…

Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   192.42 GB / 315.93 GB (60.9%)
Train Data Rows:    26090
Train Data Columns: 32
Tuning Data Rows:    1489
Tuning Data Columns: 32
```

```
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 102.65906,
210.00582)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    130409.67 MB
        Train Data (Original)  Memory Usage: 8.44 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', ['bool']) :  1 | ['is_estimated']
        0.1s = Fit runtime
        30 features in original data used to generate 30 features in processed
data.
        Train Data (Processed) Memory Usage: 6.43 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.13s …
```

```
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 599.87s of the
599.86s of remaining time.
        -28.3131         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        0.31s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 599.48s of the
599.47s of remaining time.
        -28.0892         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        0.3s     = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 599.09s of the
599.09s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.6139         = Validation score   (-mean_absolute_error)
        25.9s    = Training   runtime
        14.85s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 567.76s of the
567.76s of remaining time.
```

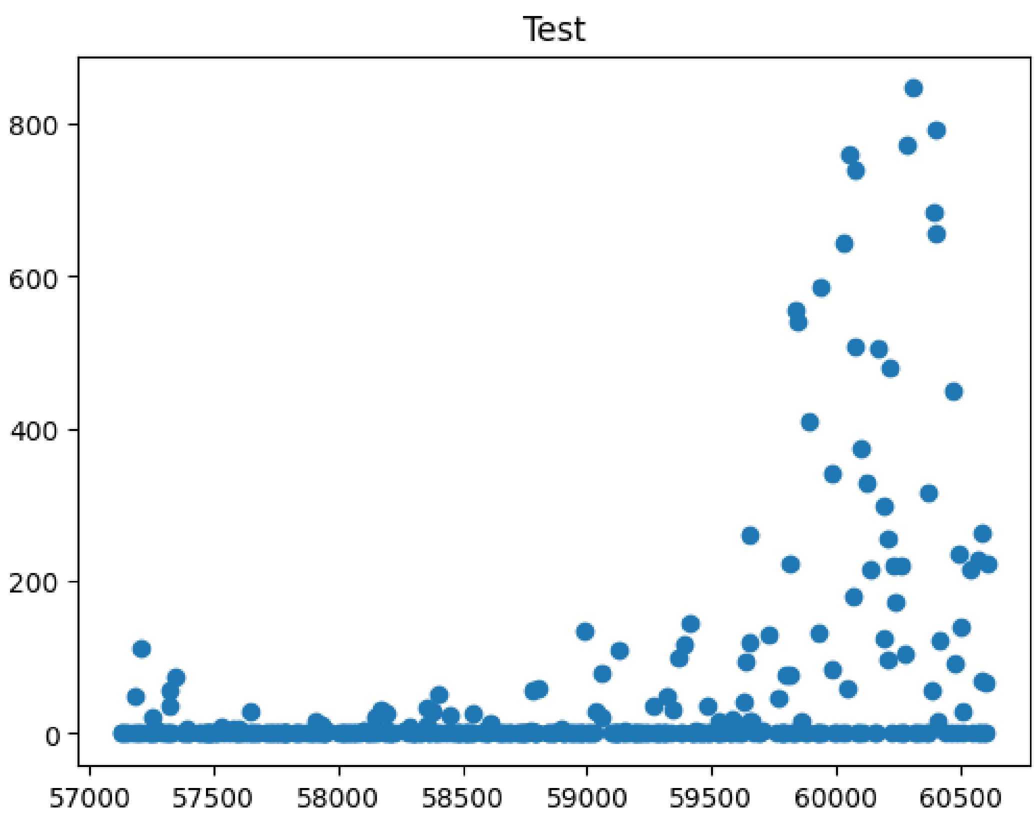
```
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.4913         = Validation score   (-mean_absolute_error)
        20.79s   = Training   runtime
        2.35s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 544.11s of
the 544.1s of remaining time.
        -14.5572         = Validation score   (-mean_absolute_error)
        5.44s    = Training   runtime
        0.85s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 536.97s of the
536.97s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.8397         = Validation score   (-mean_absolute_error)
        187.03s  = Training   runtime
        0.09s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 348.66s of the
348.66s of remaining time.
        -14.0445         = Validation score   (-mean_absolute_error)
        1.12s    = Training   runtime
        0.84s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 345.81s of
the 345.81s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.6178         = Validation score   (-mean_absolute_error)
        32.4s    = Training   runtime
        0.43s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 311.94s of the
311.93s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.8359         = Validation score   (-mean_absolute_error)
        42.67s   = Training   runtime
        1.4s     = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 266.23s of the
266.23s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.2599         = Validation score   (-mean_absolute_error)
        110.78s  = Training   runtime
        0.28s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 153.97s of the
153.97s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.0194         = Validation score   (-mean_absolute_error)
```

```
        78.22s   = Training   runtime
        10.64s   = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
68.37s of remaining time.
        -11.8259         = Validation score   (-mean_absolute_error)
        0.4s     = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 532.06s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_116_B/")
Evaluation: mean_absolute_error on test data: -10.752526683523694
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -10.752526683523694,
    "root_mean_squared_error": -32.460020162727645,
    "mean_squared_error": -1053.6529089646851,
    "r2": 0.9459186423714476,
    "pearsonr": 0.9733158998994246,
    "median_absolute_error": -0.21907338500022888
}

Evaluation on test data:
-10.752526683523694
```




```
                      model  score_test  score_val  pred_time_test  pred_time_val
fit_time  pred_time_test_marginal  pred_time_val_marginal  fit_time_marginal
stack_level  can_infer  fit_order
0       WeightedEnsemble_L2  -10.752527 -11.825878        4.185191      27.053099
248.823280                 0.004308                0.000548           0.404854
2        True         12
1         LightGBMXT_BAG_L1  -11.240628 -12.613925        1.091974      14.853881
25.896544                 1.091974               14.853881          25.896544
1        True          3
2     NeuralNetTorch_BAG_L1  -11.379913 -12.259864        0.161163       0.284024
110.783058                 0.161163                0.284024         110.783058
1        True         10
3      LightGBMLarge_BAG_L1  -12.457880 -13.019434        2.343053      10.640155
78.221396                 2.343053               10.640155          78.221396
1        True         11
4      ExtraTreesMSE_BAG_L1  -12.786492 -14.044460        0.406377       0.841873
1.121238                 0.406377                0.841873           1.121238
1        True          7
5           LightGBM_BAG_L1  -12.944931 -13.491300        0.629032       2.354633
20.794421                 0.629032                2.354633          20.794421
1        True          4
```

```
6           CatBoost_BAG_L1   -13.073780 -13.839691        0.065507        0.092974
187.025656                 0.065507                0.092974          187.025656
1        True            6
7            XGBoost_BAG_L1   -13.328093 -13.835918        0.472890        1.395476
42.671121                  0.472890                1.395476          42.671121
1        True            9
8    NeuralNetFastAI_BAG_L1   -13.443054 -13.617805        0.178316        0.432618
32.396191                  0.178316                0.432618          32.396191
1        True            8
9    RandomForestMSE_BAG_L1   -13.587345 -14.557185        0.394867        0.846941
5.438638                   0.394867                0.846941          5.438638
1        True            5
10    KNeighborsDist_BAG_L1   -26.423493 -28.089198        0.010589        0.298730
0.022912                   0.010589                0.298730          0.022912
1        True            2
11    KNeighborsUnif_BAG_L1   -26.754701 -28.313113        0.013198        0.308842
0.022734                   0.013198                0.308842          0.022734
1        True            1
```



[21]:
```
loc = "C"
predictors[2] = fit_predictor_for_location(loc)
```

```
leaderboards[2] = leaderboard_for_location(2, loc)
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=0, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 600s
AutoGluon will save models to "AutogluonModels/submission_116_C/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
```

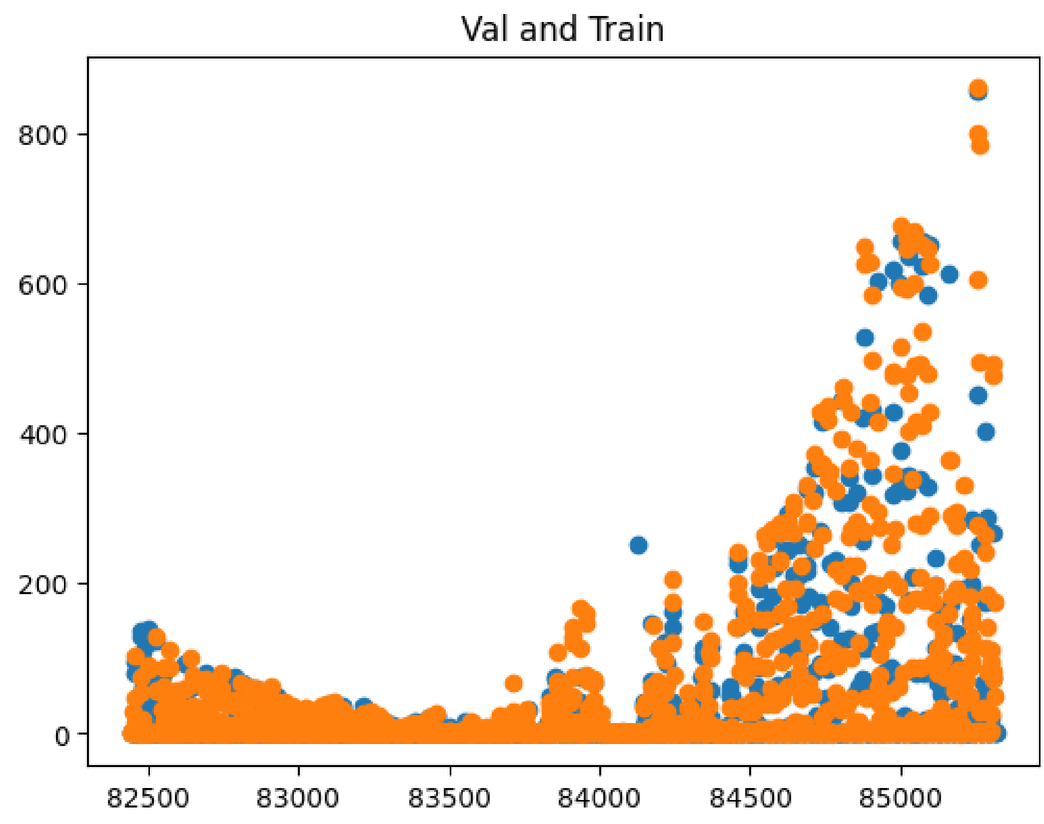
```
Training model for location C…
```

```
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   190.69 GB / 315.93 GB (60.4%)
Train Data Rows:    22830
Train Data Columns: 32
Tuning Data Rows:    1500
Tuning Data Columns: 32
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, 0.0, 84.9993, 172.88044)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    130137.47 MB
        Train Data (Original)  Memory Usage: 7.45 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
```

```
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', ['bool']) :  1 | ['is_estimated']
        0.1s = Fit runtime
        30 features in original data used to generate 30 features in processed
data.
        Train Data (Processed) Memory Usage: 5.67 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.13s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 599.87s of the
```

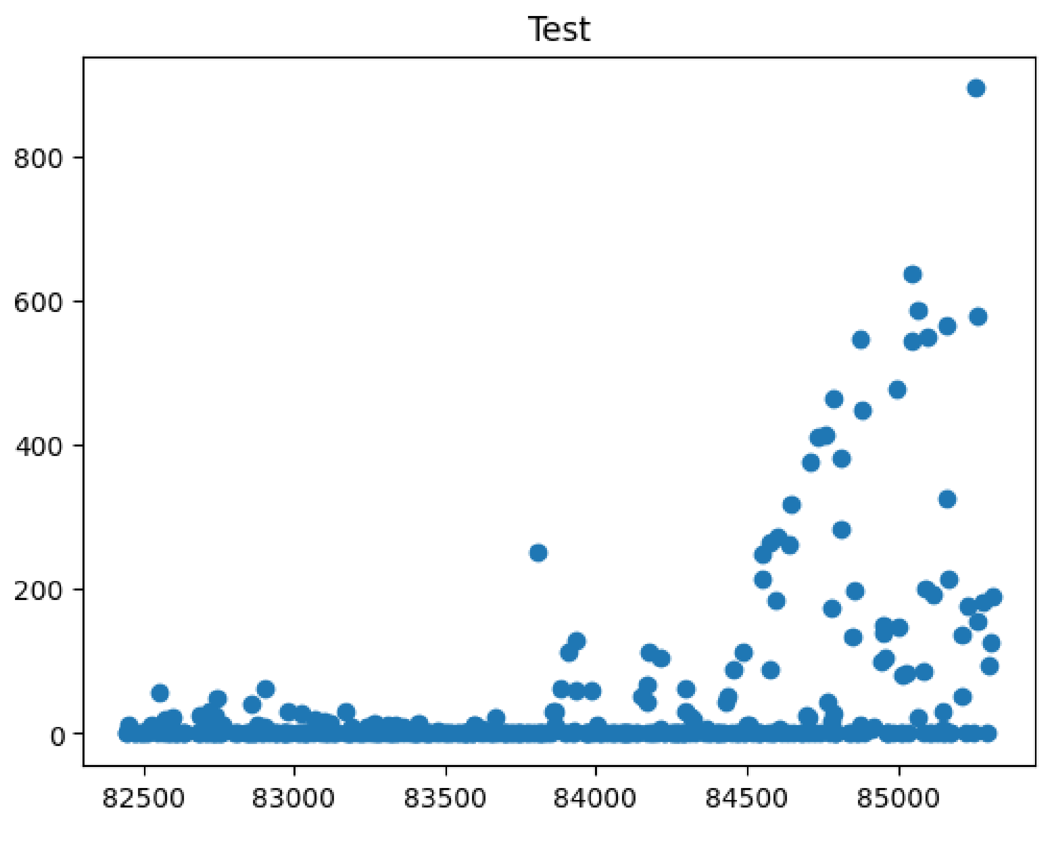
```
599.86s of remaining time.
        -21.4098         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        0.31s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 599.49s of the
599.48s of remaining time.
        -21.4688         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        0.22s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 599.18s of the
599.18s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.017  = Validation score   (-mean_absolute_error)
        25.46s   = Training   runtime
        11.99s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 569.04s of the
569.03s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.0277         = Validation score   (-mean_absolute_error)
        20.92s   = Training   runtime
        3.04s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 545.04s of
the 545.04s of remaining time.
        -16.9426         = Validation score   (-mean_absolute_error)
        4.44s    = Training   runtime
        0.71s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 539.28s of the
539.28s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.9433         = Validation score   (-mean_absolute_error)
        184.97s  = Training   runtime
        0.07s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 353.07s of the
353.07s of remaining time.
        -15.6697         = Validation score   (-mean_absolute_error)
        0.91s    = Training   runtime
        0.72s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 350.76s of
the 350.76s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.8995         = Validation score   (-mean_absolute_error)
        28.94s   = Training   runtime
        0.37s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 320.27s of the
```

```
320.27s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.5551         = Validation score   (-mean_absolute_error)
        40.76s   = Training   runtime
        1.13s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 276.88s of the
276.88s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.3338         = Validation score   (-mean_absolute_error)
        70.17s   = Training   runtime
        0.26s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 205.37s of the
205.37s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.1492         = Validation score   (-mean_absolute_error)
        77.17s   = Training   runtime
        7.86s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
121.52s of remaining time.
        -12.4438         = Validation score   (-mean_absolute_error)
        0.4s     = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 478.9s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_116_C/")
Evaluation: mean_absolute_error on test data: -16.423423115474755
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -16.423423115474755,
    "root_mean_squared_error": -45.333225477603136,
    "mean_squared_error": -2055.1013322032063,
    "r2": 0.8502733302321988,
    "pearsonr": 0.9226683058608164,
    "median_absolute_error": -0.5052815079689026
}

Evaluation on test data:
-16.423423115474755
```




```
                        model  score_test  score_val  pred_time_test  pred_time_val
fit_time  pred_time_test_marginal  pred_time_val_marginal  fit_time_marginal
stack_level  can_infer  fit_order
0       WeightedEnsemble_L2  -16.423423 -12.443783        3.420968      20.792880
202.152997                 0.004219                0.000570           0.401286
2        True         12
1         LightGBMXT_BAG_L1  -17.242135 -13.017020        0.939533      11.993397
25.455097                 0.939533               11.993397          25.455097
1        True          3
2      LightGBMLarge_BAG_L1  -17.377540 -13.149177        2.146870       7.857003
77.170267                 2.146870                7.857003          77.170267
1        True         11
3    NeuralNetTorch_BAG_L1  -17.415137 -14.333768        0.152290       0.264330
70.167785                 0.152290                0.264330          70.167785
1        True         10
4           LightGBM_BAG_L1  -17.442033 -14.027740        0.479066       3.035052
20.915712                 0.479066                3.035052          20.915712
1        True          4
5   NeuralNetFastAI_BAG_L1  -17.574354 -14.899464        0.167573       0.370983
28.936989                 0.167573                0.370983          28.936989
1        True          8
```

```
6          CatBoost_BAG_L1  -17.840705 -13.943283        0.061594       0.071216
184.966420                 0.061594                0.071216        184.966420
1        True            6
7            XGBoost_BAG_L1  -18.247367 -14.555117        0.354156       1.134426
40.762012                 0.354156                1.134426        40.762012
1        True            9
8      ExtraTreesMSE_BAG_L1  -19.561629 -15.669666        0.322408       0.721524
0.907907                 0.322408                0.721524        0.907907
1        True            7
9    RandomForestMSE_BAG_L1  -21.105039 -16.942578        0.275939       0.707568
4.440789                 0.275939                0.707568        4.440789
1        True            5
10   KNeighborsUnif_BAG_L1  -22.523308 -21.409777        0.010485       0.306598
0.021573                 0.010485                0.306598        0.021573
1        True            1
11   KNeighborsDist_BAG_L1  -22.660997 -21.468828        0.014170       0.221102
0.021338                 0.014170                0.221102        0.021338
1        True            2
```



[ ]:
```
# save leaderboards to csv
pd.concat(leaderboards).to_csv(f"leaderboards/{new_filename}.csv")
```

5 Submit

[23]:
```
import pandas as pd
import matplotlib.pyplot as plt

future_test_data = TabularDataset('X_test_raw.csv')
future_test_data["ds"] = pd.to_datetime(future_test_data["ds"])
#test_data
```

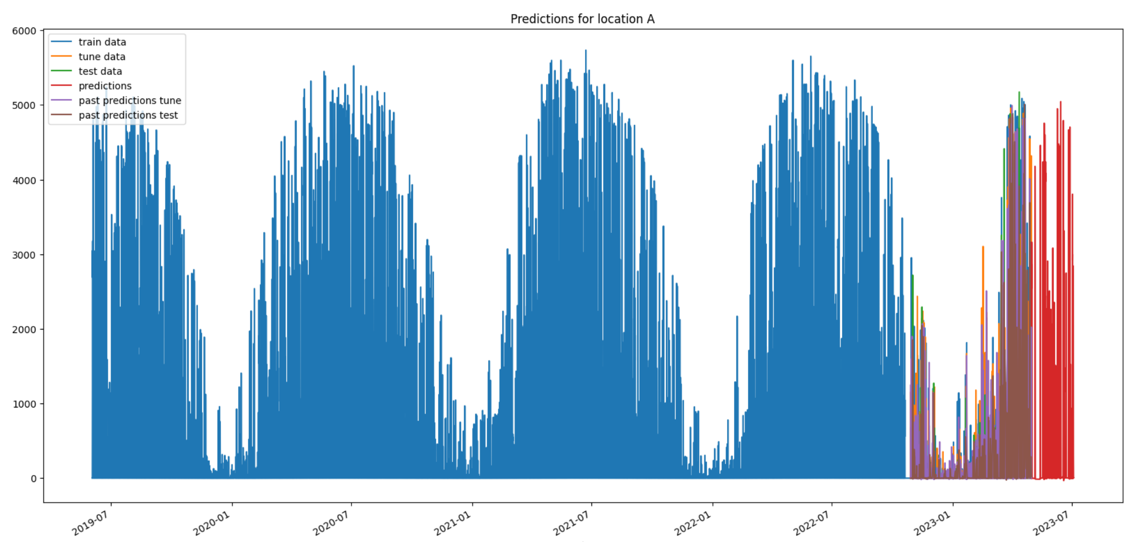
```
Loaded data from: X_test_raw.csv | Columns = 33 / 33 | Rows = 4608 -> 4608
```

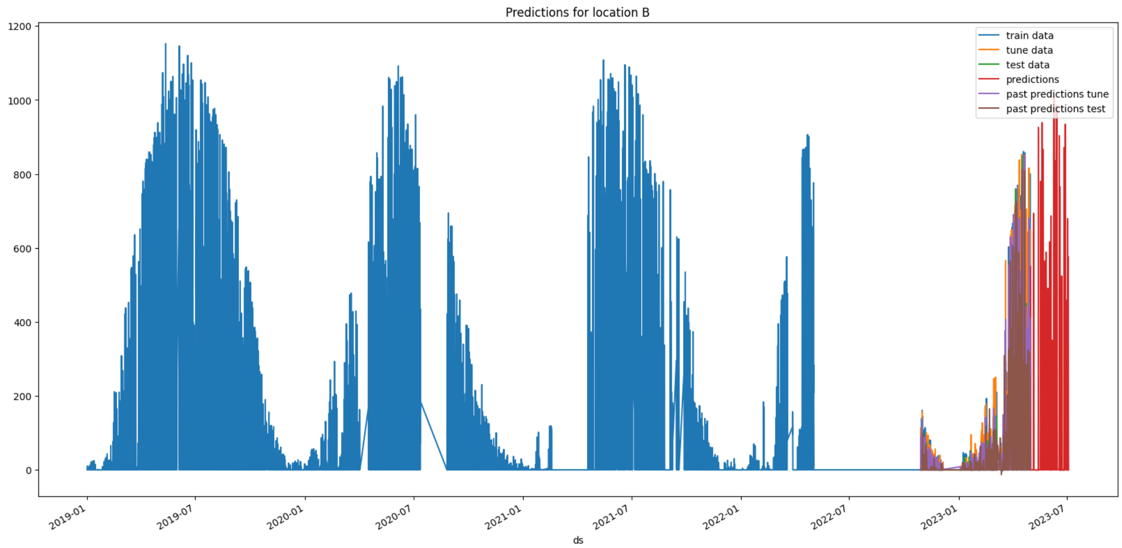
[24]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
future_test_data_merged = pd.merge(future_test_data, test_ids, how="inner",␣
↪right_on=["time", "location"], left_on=["ds", "location"])

#test_data_merged
```

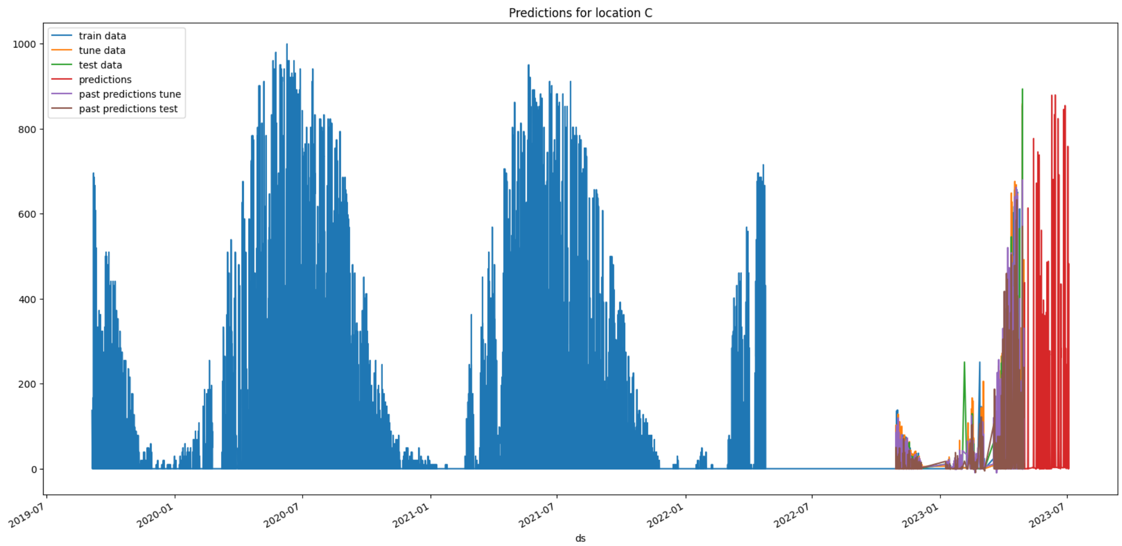
```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

[25]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in future_test_data.groupby('location'):
    i = location_map[loc]
    subset = future_test_data_merged[future_test_data_merged["location"] ==␣
↪loc].reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)

    # get past predictions
    #train_data.loc[train_data["location"] == loc, "prediction"] = ␣
↪predictors[i].predict(train_data[train_data["location"] == loc])
    if use_tune_data:
        tuning_data.loc[tuning_data["location"] == loc, "prediction"] = ␣
↪predictors[i].predict(tuning_data[tuning_data["location"] == loc])
    if use_test_data:
        test_data.loc[test_data["location"] == loc, "prediction"] = ␣
↪predictors[i].predict(test_data[test_data["location"] == loc])
```

[26]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data[train_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
↪label="train data")
    if use_tune_data:
        tuning_data[tuning_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
↪label="tune data")
    if use_test_data:
        test_data[test_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
↪label="test data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # plot past predictions
    #train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
↪y='prediction', ax=ax, label="past predictions")
    #train_data[train_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions train")
    if use_tune_data:
        tuning_data[tuning_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions tune")
    if use_test_data:
        test_data[test_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions test")


    # title
    ax.set_title(f"Predictions for location {loc}")
```







[27]:
```
temp_predictions = [prediction.copy() for prediction in predictions]
if clip_predictions:
    # clip predictions smaller than 0 to 0
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        pred.loc[pred["prediction"] < 0, "prediction"] = 0
        print("Smallest prediction after clipping:", pred["prediction"].min())
```

```python
    # Instead of clipping, shift all prediction values up by the largest negative␣
 ↪number.
    # This way, the smallest prediction will be 0.
    elif shift_predictions:
        for pred in temp_predictions:
            # print smallest prediction
            print("Smallest prediction:", pred["prediction"].min())
            pred["prediction"] = pred["prediction"] - pred["prediction"].min()
            print("Smallest prediction after clipping:", pred["prediction"].min())

    elif shift_predictions_by_average_of_negatives_then_clip:
        for pred in temp_predictions:
            # print smallest prediction
            print("Smallest prediction:", pred["prediction"].min())
            mean_negative = pred[pred["prediction"] < 0]["prediction"].mean()
            # if not nan
            if mean_negative == mean_negative:
                pred["prediction"] = pred["prediction"] - mean_negative

            pred.loc[pred["prediction"] < 0, "prediction"] = 0
            print("Smallest prediction after clipping:", pred["prediction"].min())



    # concatenate predictions
    submissions_df = pd.concat(temp_predictions)
    submissions_df = submissions_df[["id", "prediction"]]
    submissions_df
```

```
Smallest prediction: -33.170387
Smallest prediction after clipping: 0.0
Smallest prediction: -1.054768
Smallest prediction after clipping: 0.0
Smallest prediction: -0.9760284
Smallest prediction after clipping: 0.0
```

[27]:

	id	prediction
0	0	0.000000
1	1	0.000000
2	2	0.000000
3	3	7.782601
4	4	285.853760
..	…	…
715	2155	58.165791
716	2156	36.872784
717	2157	10.204181

```
718  2158    1.459767
719  2159    0.874871

[2160 rows x 2 columns]
```

[28]:
```python
# Save the submission DataFrame to submissions folder, create new name based on last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"), index=False)
print("jall1a")
```

```
Saving submission to submissions/submission_116.csv
jall1a
```

[ ]:
```python
# feature importance
# print starting calculating feature importance for location A with big text font
print("\033[1m" + "Calculating feature importance for location A..." + "\033[0m")
predictors[0].feature_importance(feature_stage="original", data=test_data[test_data["location"] == "A"], time_limit=60*10)
print("\033[1m" + "Calculating feature importance for location B..." + "\033[0m")
predictors[1].feature_importance(feature_stage="original", data=test_data[test_data["location"] == "B"], time_limit=60*10)
print("\033[1m" + "Calculating feature importance for location C..." + "\033[0m")
predictors[2].feature_importance(feature_stage="original", data=test_data[test_data["location"] == "C"], time_limit=60*10)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'location', 'prediction']
Computing feature importance via permutation shuffling for 30 features using 360
rows with 10 shuffle sets… Time limit: 600s…
```

Calculating feature importance for location A…

```
        348.81s = Expected runtime (34.88s per shuffle set)
        44.25s  = Actual runtime (Completed 10 of 10 shuffle sets)
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'location', 'prediction']
Computing feature importance via permutation shuffling for 30 features using 362
rows with 10 shuffle sets… Time limit: 600s…
```

Calculating feature importance for location B…

```
        1205.89s        = Expected runtime (120.59s per shuffle set)
```

```
        140.92s = Actual runtime (Completed 10 of 10 shuffle sets)
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'location', 'prediction']
Computing feature importance via permutation shuffling for 30 features using 364
rows with 10 shuffle sets… Time limit: 600s…
```

Calculating feature importance for location C…

```
        1022.66s        = Expected runtime (102.27s per shuffle set)
```

[ ]:
```
# save this notebook to submissions folder
import subprocess
import os
#subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
 ↪join('notebook_pdfs', f"{new_filename}_automatic_save.pdf"),␣
 ↪"autogluon_each_location.ipynb"])
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
 ↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
 ↪ipynb"])
```

[ ]:
```
# import subprocess

# def execute_git_command(directory, command):
#     """Execute a Git command in the specified directory."""
#     try:
#         result = subprocess.check_output(['git', '-C', directory] + command,␣
 ↪stderr=subprocess.STDOUT)
#         return result.decode('utf-8').strip(), True
#     except subprocess.CalledProcessError as e:
#         print(f"Git command failed with message: {e.output.decode('utf-8').
 ↪strip()}")
#         return e.output.decode('utf-8').strip(), False

# git_repo_path = "."

# execute_git_command(git_repo_path, ['config', 'user.email',␣
 ↪'henrikskog01@gmail.com'])
# execute_git_command(git_repo_path, ['config', 'user.name', hello if hello is␣
 ↪not None else 'Henrik eller Jørgen'])

# branch_name = new_filename

# # add datetime to branch name
# branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

# commit_msg = "run result"

# execute_git_command(git_repo_path, ['checkout', '-b',branch_name])
```

```
# # Navigate to your repo and commit changes
# execute_git_command(git_repo_path, ['add', '.'])
# execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# # Push to remote
# output, success = execute_git_command(git_repo_path, ['push',␣
↪'origin',branch_name])

# # If the push fails, try setting an upstream branch and push again
# if not success and 'upstream' in output:
#     print("Attempting to set upstream and push again...")
#     execute_git_command(git_repo_path, ['push', '--set-upstream',␣
↪'origin',branch_name])
#     execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

# execute_git_command(git_repo_path, ['checkout', 'main'])
```

```
[ ]:
```